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ORIGINAL ARTICLE

Power–cadence relationship in endurance cycling

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Abstract In maximal sprint cycling, the power–cadence relationship to assess the maximal power output (P_{max}) and the corresponding optimal cadence (C_{opt}) has been widely investigated in experimental studies. These studies have generally reported a quadratic power–cadence relationship passing through the origin. The aim of the present study was to evaluate an equivalent method to assess P_{max} and C_{opt} for endurance cycling. The two main hypotheses were: (1) in the range of cadences normally used by cyclists, the power–cadence relationship can be well fitted with a quadratic regression constrained to pass through the origin; (2) P_{max} and C_{opt} can be well estimated using this quadratic fit. We tested our hypothesis using a theoretical and an experimental approach. The power–cadence relationship simulated with the theoretical model was well fitted with a quadratic regression and the bias of the estimated P_{max} and C_{opt} was negligible (1.0 W and 0.6 rpm). In the experimental part, eight cyclists performed an incremental cycling test at 70, 80, 90, 100, and 110 rpm to yield power–cadence relationships at fixed blood lactate concentrations of 3, 3.5, and 4 mmol L^{-1}. The determined power outputs were well fitted with quadratic regressions ($R^2 = 0.94$–0.96, residual standard deviation = 1.7%). The 95% confidence interval for assessing individual P_{max} and C_{opt} was ±4.4 W and ±2.9 rpm. These theoretical and experimental results suggest that P_{max}, C_{opt}, and the power–cadence relationship around C_{opt} could be well estimated with the proposed method.

Keywords Pedaling rate · Optimal cadence · Power output · Lactate threshold · Performance

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Introduction

Three objectives of sport science are: (1) to identify the various human and environmental factors influencing performance; (2) to analyze the influencing effect of these factors on performance; (3) to optimize performance. Cycling science studies have already identified and analyzed numerous physiological, biomechanical, mechanical, and environmental factors that influence cycling performance. For a review of these factors see, e.g., Atkinson et al. (2003); Faria et al. (2005a, b); Jeukendrup and Martin (2001).

Cadence selection is one of the important factors in road cycling performance. To achieve a certain cycling velocity, a cyclist can either choose a high cadence and exert a low force on the pedals, or choose a low cadence and exert a high force on the pedals. Hence, cadence selection is a never-ending discussion in the theory and practice of cycling (Hansen et al. 2002a, b, 2006, 2007; Hansen and Smith 2009; Harnish et al. 2007; Hausswirth et al. 2009; Leirdal and Ettema 2009; Vercruyssen and Brisswalter 2009; Whitty et al. 2009). Accordingly, the scientific community has examined the influence of cadence on several variables during cycling to identify an optimal cadence. In these studies, the term "optimal cadence" has been defined and used from different points of view as summarized in the reviews of Abbiss et al.

(2009), Ansley and Cangley (2009), and Marais and Pelayo (2003). This inconsistent definition of “optimal cadence” leads to conflicting results concerning optimal cadence in cycling.

However, of most interest for a competitive road cyclist is the cadence that allows the greatest possible mechanical external power output (P_{ext}) to be sustained for a given task (e.g. a time trial), defined here as the optimal cadence (C_{opt}). P_{ext} includes the mechanical power output to overcome the resistive forces (rolling resistances, bearing resistances, grade resistance, and aerodynamic drag) acting on the bicycle. Furthermore, from a theoretical point of view, it is clear that the longer the task, the lower the sustainable P_{ext} will be (di Prampero 2003; Ferretti et al. 2011). To assess the two useful parameters of (i) maximum value of mechanical external power output (P_{max}) and (ii) the corresponding optimal cadence (C_{opt}), the P_{ext}–cadence relationship for the given task must be identified.

In maximal sprint cycling, the P_{ext}–cadence relationship has been widely investigated in experimental studies (Dorel et al. 2005, 2010; Gardner et al. 2007; Hintzy et al. 1999; MacIntosh and Fletcher 2011; MacIntosh et al. 2003, 2004; Martin et al. 1997). These studies generally have reported a quadratic P_{ext}–cadence relationship passing through the origin. In endurance cycling, only a few studies have compared P_{ext} between the single cadences. Watson and Swensen (2006) compared the 5-mile time trial P_{ext} among preferred cadence (PC), PC + 10%, and PC − 10%. Mora-Rodriguez and Aguado-Jimenez (2006) compared P_{ext} at the second ventilatory threshold among 80, 100, and 120 rpm. Denadai et al. (2006) compared P_{ext} at maximal lactate steady state (MLSS) between 50 and 100 rpm. They all showed that cadence has a significant influence on P_{ext}, but they did not investigate the P_{ext}–cadence relationship to assess C_{opt} and P_{max}. To the best of our knowledge, no experimental study has analyzed the P_{ext}–cadence relationship in endurance cycling to assess C_{opt} and P_{max}.

The aim of the present study was to evaluate a method to assess P_{max} and C_{opt} for endurance cycling. Our two main hypotheses were: (1) in the range of cadences normally used by cyclists during races or training (70–110 rpm), the P_{ext}–cadence relationship can be well fitted with a quadratic regression constrained to pass through the origin; (2) the precision of the estimated values of P_{max} and C_{opt} assessed with this fit is high enough to detect even small, but relevant shifts in P_{max} and C_{opt} under different conditions. We tested our two main hypothesis using: (1) a theoretical approach with a simplified cycling model based on Hill’s muscle model and Minetti’s internal power model and (2) in experimental tests with the comparison of P_{ext} at fixed blood lactate thresholds (LT_{fix}) among different cadences.

Methods

Model

A simplified, planar two-legged bicycle-rider model (Fig. 1) based on the lower extremity model developed by Delp et al. (1990) was used with OpenSim (OpenSim 2.0, Simtk.org). Each leg included three rigid-body segments (thigh, shank, and foot). The pelvis and the crank axis were fixed and the feet rigidly attached to the pedals. The position and orientation of the pelvis in relation to the crank axis, and the segment lengths were taken from a cyclist of 1.75 m height and 70 kg mass. Because of the closed loops, the model had only three degrees of freedom: the crank angle (θ_C), and the left and right pedal angles (α_l, α_r). To further constrain the model, the pedal angles were related to the crank angle according to the proposed equation of Redfield and Hull (1986):

$$\alpha = A_1 \cdot \sin(\theta_C) + A_2 \cdot \cos(\theta_C) + A_3 \qquad (1)$$

where A_1, A_2, and A_3 are constants to be assessed. Each leg was provided with 18 muscles: iliacus, psoas, gluteus maximus, gluteus medius, gluteus minimus, biceps femoris long head, biceps femoris short head, semimembranosus, semitendinosus, rectus femoris, vastus lateralis, vastus medialis, vastus intermedius, gastrocnemius lateralis,

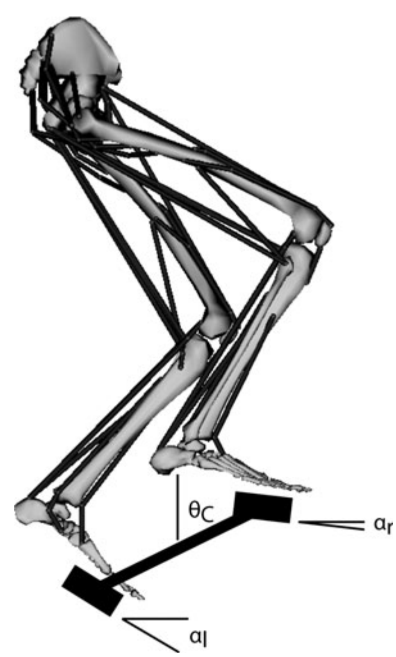

Fig. 1 A planar two-legged cycling model based on the lower extremity OpenSim model (Delp et al. 1990) was used. The lower limbs were modeled as a three-segment (thigh, shank, and ankle-pedal) rigid-body system. The pelvis was fixed relative to the crank axis. The model had three independent degrees of freedom, the crank angle (θ_C), and the left and right pedal angles (α_l, α_r). Eighteen muscle–tendon units were included

gastrocnemius medialis, soleus, tibialis posterior, and tibialis anterior. The force-generating capacity of these muscles was based on the force–velocity characteristics of muscles, described by the hyperbolic equation and first presented by Hill (1938). According to Phillips and Petrofsky (1980), an activation level including Henneman's size principle (Henneman and Olson 1965; Mendell and Henneman 1971) was added to Hill's equation to be able to calculate the active force in dependence on the degree of activation (Denoth 2008):

$$\begin{aligned} F_a &= b \cdot (F_0 + a)/(v + b) - a \\ &\text{with} \\ F_0 &= F_{0,\max} \cdot Z \\ a &= (k_1 + k_2 \cdot Z) \cdot F_{0,\max} \\ b &= \left(k_3 + k_4 \cdot Z + k_5 \cdot Z^2\right) \cdot l_0 \end{aligned} \tag{2}$$

where F_a (N) is the active force of the muscle, v (m s^{-1}) is the shortening velocity of the muscle, $F_{0,\max}$ (N) is the maximal isometric force depending on the cross-sectional area of the muscle and on the muscle length in relation to its optimal length (force–length relation), Z is the activation level, a (N) and b (m s^{-1}) are constants determining the force–velocity relationship, k_1, k_2, k_3, k_4 and k_5 are constants depending on the fiber type composition of the muscle, l_0 (m) is the optimal fiber length of the muscle. The potential power output of a muscle is defined as:

$$P_{\mathrm{m}} = \left(F_a + F_{\mathrm{p}}\right) \cdot v \tag{3}$$

where F_{p} (N) is the passive force of the muscle depending on the muscle length in relation to its optimal length. The values of $F_{0,\max}$ and F_{p} of each single muscle in relation to its length were taken from the lower extremity model developed by Delp et al. (1990). With Eqs. 2 and 3, the power–velocity relationship for isotonic muscle contraction is obtained. During repetitive contraction, such as during cycling, the muscle shortening velocities are not constant throughout the shortening phase. For cyclic movements, the shortening trajectories are sinusoidal or nearly so, depending on the joint kinematics and the moment arm of the muscles. Thus, the shortening velocities of the muscles in our constrained model depend on the crank angle (θ_{C}), the crank angle velocity ($\mathrm{d}\theta_C/\mathrm{d}t$), and the constants of Eq. 1.

During the cycling simulations, the cranks in our model were actuated with a constant angular velocity, and only the uniarticular muscles were active in their shortening phase. Thus, with the constants Z, a, b, A_1, A_2, and A_3 assessed (Table 1), the power output of each single muscle can be calculated.

By calculating the mean total muscular power output over an entire crank cycle for different constant angular velocities of the cranks, we get a power–cadence relationship for the total muscular power output (P_{tot}). This P_{tot}–cadence relationship per se has no practical use for the competitive cyclists. The cyclists are not interested in the cadence at which they can produce the highest muscular power output, but they are interested in $P_{\max}$ and the corresponding C_{opt} of the P_{ext}–cadence relationship. To get the relevant power–cadence relationship for the mechanical external power output, the mechanical internal power output (P_{int}) has to be subtracted (Fig. 2):

$$P_{\mathrm{ext}} = P_{\mathrm{tot}} - P_{\mathrm{int}} \tag{4}$$

As mentioned by Minetti (2011), P_{int} is an often neglected and almost immeasurable portion of P_{tot} that could be proportional to the "kinematic" form. P_{int} was estimated by measuring the mechanical or metabolic energy changes in various studies. The pedaling frequency (Foss and Hallen 2004; Hansen et al. 2004; Minetti et al. 2001; Prampero et al. 1979; Tokui and Hirakoba 2007, 2008), the mass of the legs (Francescato et al. 1995; Kamon et al. 1973), and the gravity acceleration (Bonjour et al. 2010; Girardis et al. 1999)

Table 1 Constants used for the simulation

Z	$k1$	$k2$	$k3$	$k4$	$k5$	A_1	A_2	A_3
0.75	0.1	0.07	0.3	2.35	−1	−0.34	0.10	0.29

Z, activation level of the muscles (Eq. 2); $k1$, $k2$, $k3$, $k4$ and $k5$, constants determining the shape of the force–velocity relationship of the muscles (Eq. 2); A_1, A_2, and A_3, constants determining the pedal angle in relation to the crank angle (Eq. 1)

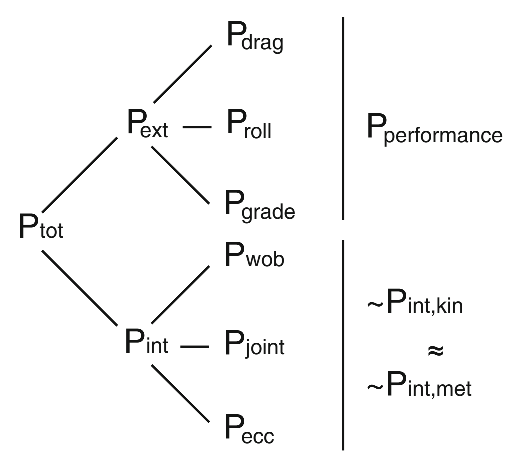

Fig. 2 The power cascade. P_{tot} muscular concentric power output, P_{ext} mechanical external power output, P_{drag} power output needed against aerodynamic drag, P_{roll} power output needed against rolling resistances, P_{grade} power output needed against grade resistance, P_{int} mechanical internal power output, P_{wob} Dissipation of kinetic energy of wobbling masses, P_{joint} power output needed against viscous/frictional resistance of joint cartilage, ligaments, and other extramuscular structures of the joints, P_{ecc} muscular eccentric power output, $P_{\mathrm{performance}}$ performance power output, $P_{\mathrm{int,kin}}$ kinematic internal power, $P_{\mathrm{int,met}}$ metabolic internal power

were identified as three of the determinants of P_{int}. Minetti et al. (2001) estimated P_{int} for cycling on a standard racing bicycle using a kinematic approach ('kinematic internal power'). They suggested the following equation to estimate P_{int}:

$$P_{int} = 0.153 \cdot (C/60)^3 \cdot \mathrm{BM} \qquad (5)$$

where C (rpm) is the pedaling cadence and BM (kg) is the body mass. By inserting Eq. 5 into Eq. 4, we obtain the power–cadence relationship for P_{ext}. This relationship simulated with our model shows a nearly quadratic form (Fig. 3a). The simulation calculated P_{ext} from 0 to 200 rpm with a resolution of 0.1 rpm. This simulated P_{ext}–cadence relationship was used to assess the simulated P_{max} ($P_{max,\ sim}$) and C_{opt} ($C_{opt,\ sim}$). In the experimental part of the study, it is unrealistic to measure the power output at such a high number of different cadences. To assess P_{max} and C_{opt} in an experimental approach, the P_{ext}–cadence relationship must be fitted to a restricted number of measured power outputs at different cadences. Looking only at the range of cadences normally used by cyclists during cycling on level ground (70–110 rpm; (Leirdal and Ettema 2009; Lucia et al. 2001; Sassi et al. 2009), the simulated P_{ext}–cadence relationship is very well fitted by a quadratic regression constrained to pass through the origin (maximal difference of 2.1 W; Fig. 3b). P_{max} and C_{opt}, the two parameters of interest, were well estimated by the use of this quadratic fit. The differences between the simulated ($P_{max,\ sim}$ and $C_{opt,\ sim}$) and the fitted values ($P_{max,\ fit}$ and $C_{opt,\ fit}$) were almost negligible (1.0 W and 0.6 rpm).

These results suggest that P_{max}, C_{opt}, and the P_{ext}–cadence relationship around C_{opt} could be well estimated by fitting experimentally measured power outputs at different cadences (in a range normally used by cyclists during races or training) with a quadratic regression constrained to pass through the origin.

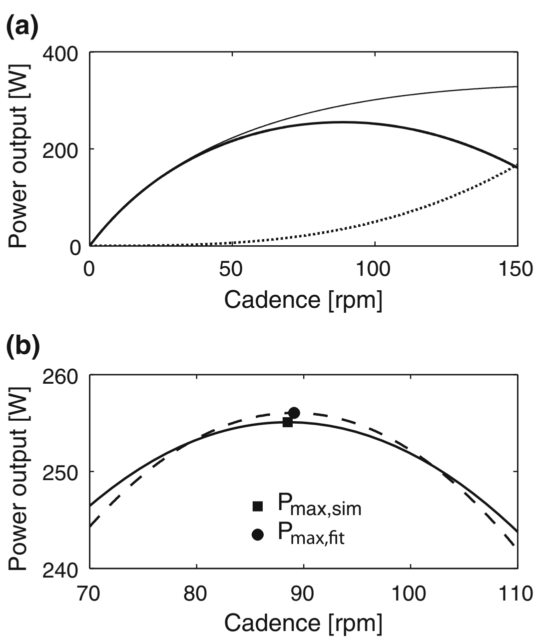

Fig. 3 **a** The simulated power–cadence relationships. The total muscular power output simulated with the OpenSim model is represented by the *thin solid line*. The internal power output calculated with Minetti's equation is shown by the dotted line. The difference in these two curves defines the power–cadence relationship of the mechanical external power output (*thick solid line*). **b** The simulated external power–cadence relationship (*solid line*) was used to assess the simulated maximal power output ($P_{max,sim}$) and the corresponding simulated optimal cadence (*square*). The simulated external power outputs in the range of cadences normally used by the cyclists (70–110 rpm) were fitted with a quadratic regression constrained to pass through the origin (*dashed line*). This quadratic regression was used to assess the fitted maximal power output ($P_{max,fit}$) and the corresponding fitted optimal cadence (*circle*)

Experiments

Subjects

Eight well-trained male amateur cyclists (26 ± 5 years, 178.5 ± 2.1 cm, and 69.7 ± 2.4 kg) volunteered to participate in this study. They were all informed of the nature about the study, and the possible risk and discomfort associated with the experimental procedures before they gave their written consent to participate. The ethical committee of ETH Zurich approved the study experimental design.

Experimental design

The purpose of these tests was to compare the mechanical external power output at LT_{fix} between the different cadences. Therefore, each participant performed an identical incremental exercise test at each of five cadences (70, 80, 90, 100, and 110 rpm) to assess P_{ext} at LT_{fix}. The subjects were asked to come to the five test sessions within a 3-week period to minimize any change in constitution. The tests were performed in randomized order at least 2 days between the test days. To improve the reliability of the lactate measurements, participants were requested to control a number of variables. They were instructed to consume a normal diet during the 48 h prior to each test session; to refrain from ingestion of caffeine for at least 4 h prior to testing; to perform workouts of similar duration and intensity on the day prior to each session; and not to perform prior exercise on the test days. To minimize variation due to circadian rhythms, each test session was conducted at the same time of the day.

For each test session, after a short warm-up, the participant had to complete an incremental exercise test with a preset pedaling rate (70, 80, 90, 100, or 110 rpm). This test was started at 100 W with an increase of 30 W every 8 min until the participant told us that he would not be able to finish the next higher stage. Blood lactate concentration (bLa) was measured at the end of each stage by taking capillary blood samples (20 μL) from the earlobes.

For each incremental exercise test, the bLa values were plotted against power output (Fig. 4a). A third-order polynomial curve was then constructed from these data points (Thomas et al. 2008). The power outputs at LT_{fix} were determined as the power outputs eliciting a bLa of 3 (LT_3), 3.5 ($LT_{3.5}$), and 4 mmol L^{-1} (LT_4). For each of the three LT_{fix}, the corresponding power outputs were plotted against the used cadences (Fig. 4b). A quadratic regression constrained to pass through the origin was then fitted to assess individual P_{max} and C_{opt} at each LT_{fix}.

Equipment

The incremental exercise tests were performed on a standard racing bicycle equipped with a professional version (8 strain gages) SRM PowerMeter (Schoberer Rad Messtechnik, Jülich, Germany), which was mounted on an indoor trainer (Flow, Tacx, Wassenaar, Netherlands). The vertical and horizontal position of the saddle and the handlebar related to the crank axis were set to match each subject's own bicycle. The lactate concentration in the blood samples was analyzed with BIOSEN C-Line (EKF Industrie-Elektronik, Barleben, Germany).

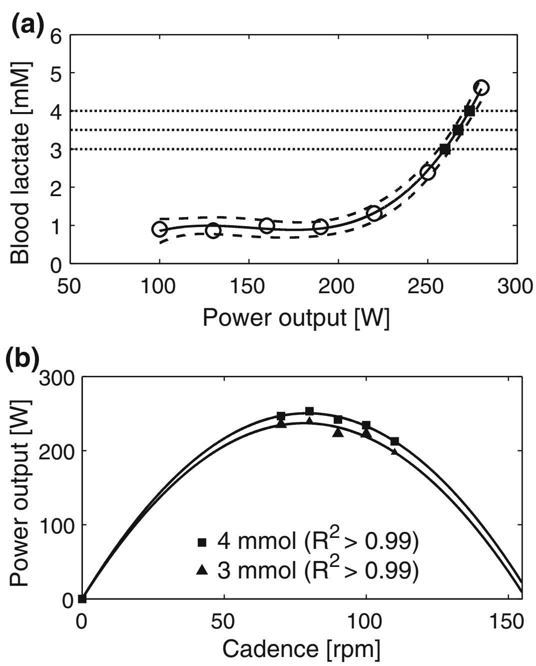

Fig. 4 **a** Measured blood lactate concentration (bLa) during the incremental cycling test with 70 rpm from a single representative subject (*open circles*). The *solid line* shows the third-order polynomial regression of these data ($R^2 > 0.99$; $P < 0.001$). The *dashed lines* mark the 95% confidence interval of the regression line. The power outputs at 3, 3.5, and 4 mmol L^{-1} (*filled squares*) were estimated from the *regression line*. **b** The power–cadence relationships of a single subject. The estimated power outputs at 3 (*triangles*) and 4 mmol L^{-1} (*squares*) with the five cadences (70, 80, 90, 100, and 110 rpm) are shown. For each bLa, a second-order polynomial regression (constrained to pass through the origin) is fitted to assess the maximal power output and the corresponding optimal cadence

Statistics

All statistics were done in SPSS Statistics 17 (SPSS Inc., Chicago, USA). The level of significance was set at $P < 0.05$. Quadratic power–cadence regressions constrained to pass through the origin were fitted by the least-squares method. Measured power output and cadence from each subject were normalized to their estimated individual P_{max} and corresponding individual C_{opt} to assess the validity of the quadratic regression constrained to pass through the origin at each LT_{fix}.

The residuals of the quadratic fit were normalized to the corresponding fitted power outputs and analyzed in a modified Bland–Altman plot (Gardner et al. 2007). The standard deviation (SD) of these residuals (residual SD) was calculated to estimate the variability of the measured power outputs. The 95% confidence interval for assessing individual P_{max} and C_{opt} was calculated using the model-based residual bootstrapping method for regression. P_{max} and C_{opt} at the different LT_{fix} were statistically analyzed using a one-factor-repeated-measures ANOVA with the Bonferroni correction for multiple comparisons as a post hoc test. Dependent variables were summarized using descriptive statistics (mean ± SD).

Results

Power output and cadence from all subjects normalized to their estimated individual P_{max} and corresponding individual C_{opt} were well fitted by a quadratic regression constrained to pass through the origin ($R^2 = 0.94$–0.96; $P < 0.001$; Fig. 5). The normalized residuals are displayed in the modified Bland–Altman plot (Fig. 6). The residual SD values were 1.7, 1.7, and 1.8% at LT_3, $LT_{3.5}$, and LT_4, respectively. The residual bootstrap method based on the mean residual SD at LT_3, $LT_{3.5}$, and LT_4 (1.7%) yielded a 95% confidence interval for assessing individual P_{max} and C_{opt} of 3.4 and 7.5%.

The assessed individual P_{max} values were 249 ± 31, 258 ± 31, and 266 ± 32 W for LT_3, $LT_{3.5}$, and LT_4, respectively. The corresponding individual C_{opt} values were 76 ± 5.2, 77 ± 5.1, and 78 ± 5.4 rpm. The repeated-measures ANOVA revealed a significant influence of performance level (LT_{fix}) on P_{max} ($P < 0.001$) and C_{opt}

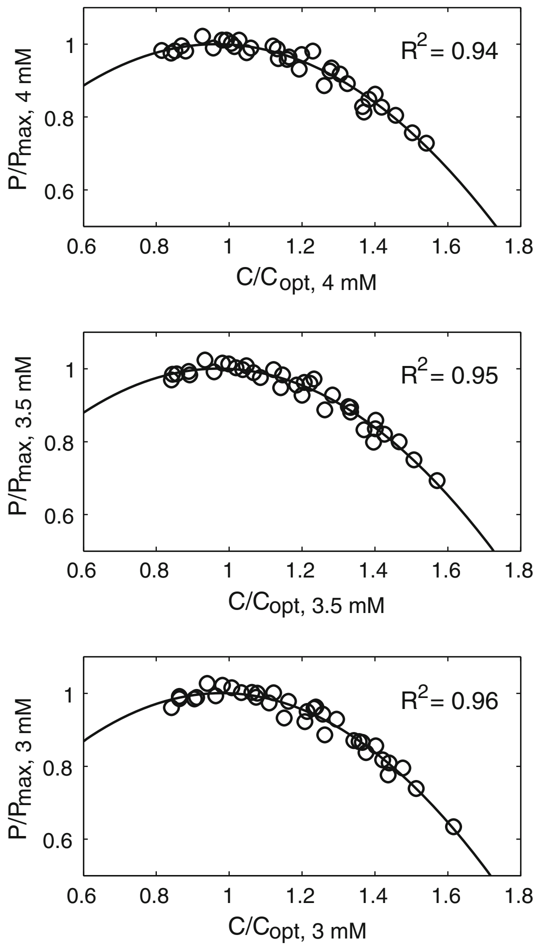

Fig. 5 Power output in relation to cadence. Power output and cadence from each subject were normalized to their estimated individual maximal power output and corresponding individual optimal cadence (Fig. 4b). The *solid lines* show the quadratic regressions constrained to pass through the origin ($R^2 = 0.94$–0.96; $P < 0.001$). The normalized power–cadence relationships at blood lactate concentrations of 3, 3.5, and 4 mmol L^{-1} are illustrated in the *single figures*

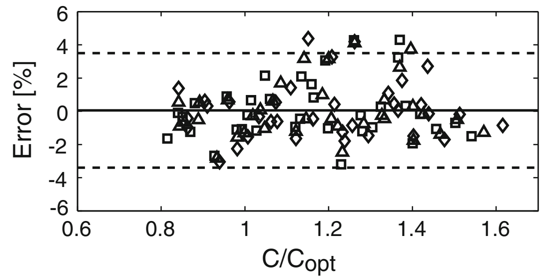

Fig. 6 Modified Bland–Altman plot of the normalized residuals (error%) of the quadratic power–cadence fit at the fixed blood lactate concentrations of 3 (*diamonds*), 3.5 (*triangles*), and 4 (*squares*) mmol L^{-1}. The *solid line* represents the mean error% (0.0 ± 1.7%). The *dashed lines* mark the 95% limits of agreement (0.0 ± 3.4%)

($P < 0.05$). Post-hoc analysis showed that P_{max} was significantly different ($P < 0.001$) between each of the LT_{fix} and that C_{opt} was significantly lower ($P < 0.05$) at LT_3 than at $LT_{3.5}$ and LT_4.

Discussion

Model

In the simplified cycling model used in this study, the P_{int}–cadence relationship is an important factor determining the P_{ext}–cadence relationship. As mentioned in the "Methods", P_{int} is an often neglected and almost immeasurable portion of P_{tot} that could be proportional to the "kinematic" form (Minetti 2011). P_{int} includes mainly three parts (Fig. 2): (1) dissipation of kinetic energy of wobbling masses (Gruber et al. 1998) through each crank revolution (kinetic part); (2) power output needed against the frictional/viscous resistance of joint cartilage, ligaments, and other extramuscular structures of the joints (viscous part); and (3) the concomitant agonist–antagonist activation, respectively, the muscular eccentric power output (coordination part). Most of the studies dealing with the biomechanics of cycling used a rigid body model to estimate P_{int} by calculating the energy changes of moving body segments based on the kinematic measurements ('kinematic internal power'). In these studies, it has been reported that P_{int} increases significantly as a power function of the cadence, but the calculated values of P_{int} are considerably different for various biomechanical models, reflecting the different methods for estimation of P_{int} in cycling (Hansen et al. 2004). As mentioned by Kautz and Neptune (2002), the kinematic approach using a rigid body model is an invalid method to measure the energy cost of moving the legs in pedaling. In a rigid body model with frictionless joints no kinetic energy is dissipated during pedaling (Kautz and Neptune 2002; Minetti 2011). However, during pedaling soft-tissue masses of the body undergo damped oscillations. And these soft-tissue deformations dissipate kinetic energy (Zelik and Kuo 2010). The kinetic, viscous, and coordination part of P_{int} cannot be measured directly, but as stated by Minetti (2011) the sum of these unmeasurables mechanical power outputs seems to be proportional to the meaningless measurable 'kinematic internal power'. In this recent publication, Minetti estimated P_{int} for cycling using a metabolic approach. The suggested equation based on the metabolic measurements ('metabolic internal power') resulted to be very close to Eq. 5 based on the kinematic measurements:

$$P_{int} = 0.150 \cdot (C/60)^3 \cdot \mathrm{BM} \quad (6)$$

Hansen et al. (2004) suggested that the metabolically based calculation of P_{int} may be used as "a gold standard" in validation of biomechanical estimations of P_{int}. Their values based on metabolic calculation were also well fitted by the equation of Minetti et al. (2001) ($R^2 > 0.99$; $P < 0.001$). This equation also has the advantage that input for the equation is restricted to cadence and body mass. With adjustment of the constant of this equation (Eq. 5) from 0.153 to 0.176, the values of Hansen et al. (2004) were even somewhat better fitted, but such a change of this constant in our simplified model has almost no influence on the shape of the P_{ext}–cadence relationship. Here it must be stated that by including Eq. 5 into the model it is assumed that P_{int} is not influenced by P_{tot}, respectively, by P_{ext}. The influence of P_{ext} on P_{int} cannot be measured directly, but Hansen et al. (2004) showed that an increase of P_{ext} of 75% had only a small effect on P_{int} (8%) estimated with different kinematic models. Furthermore, in their study P_{int} calculated with the metabolic approach was not influenced by P_{ext}. Thus, the used assumption seems to be a valid simplification for our model, respectively, for the aim of the present study.

Several experimental studies have indicated that the freely chosen cadence (FCC) increases with increasing power output, as summarized in the review of Hansen and Smith (2009). Assuming that cyclists choose a cadence near to C_{opt}, then C_{opt} should also increase with increasing power output. Theoretical studies based on the isotonic power–velocity relationship of muscle have indicated that C_{opt} should shift to higher cadences as performance level increases (Kohler and Boutellier 2005; MacIntosh et al. 2000; Sargeant 1994). The shift to a higher C_{opt} was explained by the need to recruit additional fast-twitch muscle fibers, which have a higher optimal shortening velocity compared to the more fatigue-resistant slow-twitch muscle fibers. Our model can confirm that one reason for the shift to a higher C_{opt} with increasing power output could be the additional recruitment of fast-twitch muscle fibers with increasing activation level (Henneman's size principle). On the other hand, our model points out that the P_{int}–cadence relationship could build the basis of a second possible mechanism for a shift to a higher C_{opt}. By increasing P_{ext} in a simulation including only one fiber type, the ratio of P_{ext} to P_{tot} increases and C_{opt} therefore shifts towards the higher optimal cadence of the P_{tot}–cadence relationship.

In addition, with this model, the individuality of C_{opt} caused by individual factors can easily be demonstrated. The effects of these factors on C_{opt} are not shown in this paper, but it can be inferred from the equations that cross-sectional area, fiber type composition, and moment arm of the muscle, coordination, segment lengths, and bicycle settings can influence C_{opt}. Thus, the practice of copying the cadence adopted by the best professional cyclists cannot be supported. Furthermore, the model shows that P_{max} can be increased by two ways: (1) increasing the muscular concentric power output (P_{tot}) and (2) decreasing the mechanical internal power output (P_{int}). As stated above P_{int} consists mainly of three parts: a kinetic, a viscous, and a coordination part. The most effective way to decrease P_{int} seems to be the minimization of the concomitant agonist–antagonist activation, respectively, of the muscular eccentric power output. The other two parts of P_{int} seem to be very robust intrinsic individual properties of cyclists/humans.

Experiments

The aim of the experimental part of the present study was to investigate the mechanical external power–cadence relationship at different performance levels in endurance cycling. To obtain valid P_{ext}–cadence relationships at different performance levels, an adequate, valid, and reliable indicator of endurance cycling performance had to be identified. In this circumstance, when P_{ext} at different cadences must be measured, adequacy is achieved if the indicator can be measured during one single test. Validity is obtained if the indicator shows a high correlation with endurance performance. In addition, a high accuracy of the indicator of endurance performance should be achieved. Another important consideration in determining the appropriate indicator is the reliability obtained with repeated measurement. An indicator satisfying these requirements is the mechanical external power output at fixed bLa of an incremental exercise test (LT_{fix}). With this indicator, the P_{ext} at different performance levels can be estimated during one single incremental exercise test. The validity of this indicator has been shown by a high correlation with endurance performance (Faude et al. 2009; McNaughton et al. 2006) and high accuracy for endurance performance (Lajoie et al. 2000). The reliability at LT_4 was shown by a coefficient of variation of only 1.4% across the three testing sessions (Pfitzinger and Freedson 1998). Furthermore, Denadai et al. (2006) showed that MLSS was not influenced by the different pedal cadences analyzed. Thus, mechanical external power output corresponding to fixed bLa can be considered as a good indicator for comparing endurance cycling performance among the different cadences. On the one hand, it has to be taken into account that P_{ext} corresponding to a fixed bLa could mean different performance levels for the different subjects. On the other hand for the aims of this study it is not really important, that the analyzed performance levels at fixed values of bLa show slight inter-individual differences. The individual absolute values of P_{max} and C_{opt}, which were influenced by the performance level, were not really interest in this study. The normalized relationships between cadence and power output for endurance cycling within each single subject were of interest. Thus, within a single subject the same performance level had to be compared between different cadences, but slight inter-individual differences in the analyzed performance levels were meaningless for the purpose of this study. The results approved, that the normalized P_{ext}–cadence relationship seems to be independent of the analyzed endurance performance level (LT_3, $LT_{3.5}$, or LT_4).

Assuming a quadratic P_{ext}–cadence relationship for endurance cycling and a coefficient of variation for each determined P_{ext} at LT_{fix} of 1.4% (Pfitzinger and Freedson 1998), the residual bootstrap method revealed that the 95% confidence interval for assessing individual P_{max} and C_{opt} would be 2.8 and 6.1%. In our tests, assuming a quadratic P_{ext}–cadence relationship, the mean variability of the determined P_{ext} (residual SD) at LT_3, $LT_{3.5}$, and LT_4 was somewhat higher (1.7%), resulting in a lowered precision for assessing individual P_{max} and C_{opt} (95% confidence interval of 3.4 and 7.5%). With a mean P_{max} of 258 W and a mean C_{opt} of 77 rpm, the absolute values of the 95% confidence interval were 8.8 W and 5.8 rpm. This confidence interval depends strongly on the reliability of assessing mechanical external power outputs at the defined threshold. Furthermore, the reliability of these assessments is dependent on biological and technical variability. In the case of the lactate thresholds used, a variety of factors influence the biological variability, including carbohydrate intake, caffeine intake, prior exercise, hydration status, and training status. Factors influencing the technical variability are sweat contamination of the blood sample, precision of the lactate analyzer, and the number of data points on the bLa-power plot. Each of these factors must be considered and controlled to the degree possible to minimize the 95% confidence interval for assessing individual P_{max} and C_{opt}. The established criteria for minimizing variability in the present study are described in the "Methods". The slightly higher variability found in this study compared to the reliability study of Pfitzinger and Freedson (1998) could be the result of the number of exercise tests conducted. In the present study, five incremental exercise tests were conducted whereas in the Pfitzinger and Freedson study, only three tests were performed. The greater the number of tests, greater is the possible change in the constitution of the subjects during the testing period, which influences the variability of assessing the threshold power outputs.

The results of this study suggest that individual P_{max}, C_{opt}, and the power–cadence relationship around C_{opt} can be well estimated by fitting measured power outputs at different cadences (in a range normally used by cyclists during races or training) with a quadratic regression constrained to pass through the origin. This hypothesis can also be confirmed with the analysis of experimental data from other studies that have compared P_{ext} in endurance cycling among three cadences (Mora-Rodriguez and Aguado-Jimenez 2006; Watson and Swensen 2006). The data from these studies are well fitted with a quadratic P_{ext}–cadence relationship (Fig. 7; $R^2 = 0.98$; $P < 0.001$). Furthermore, the quadratic relationship between performance and cadence can also be seen in experimental studies that compared muscle activity (MacIntosh et al. 2000; Marsh and Martin 1995; Neptune et al. 1997), neuromuscular fatigue (Takaishi et al. 1996), bLa at constant P_{ext} (Chavarren and Calbet 1999; Whitty et al. 2009), and time to exhaustion at constant P_{ext} (Foss and Hallen 2004; Nielsen et al. 2004). All of the single data sets of these studies are well fitted with a second-order polynomial regression ($R^2 = 0.88$–0.99).

Our experimental results showed a significant influence of performance level on C_{opt}. This experimental result is in agreement with the result of our simplified cycling model and with the results of other theoretical studies based on muscle force–velocity properties (Kohler and Boutellier 2005; MacIntosh et al. 2000; Sargeant 1994). This increasing C_{opt} can be compared with the increasing FCC found in other experimental studies, where increasing power outputs were achieved at least in part by increasing the gear ratio of the bicycle (Harnish et al. 2007; Leirdal and Ettema 2009). These studies found an increase of FCC with increasing power output of 8–13 rpm per 100 W. Our results showed a linear increase of C_{opt} of about 11 rpm per 100 W with increasing performance level by means of increasing bLa at LT_{fix}. This value lies in the range of the values found for the increase of FCC and has a practical relevance for competitive cyclists and also for investigators using cycling tests. Here it must be stated, that according to our model the amount of the increase of C_{opt} should show inter- (e.g. fiber type composition) and intra-subject (e.g. absolute power output) variability. As mentioned above,

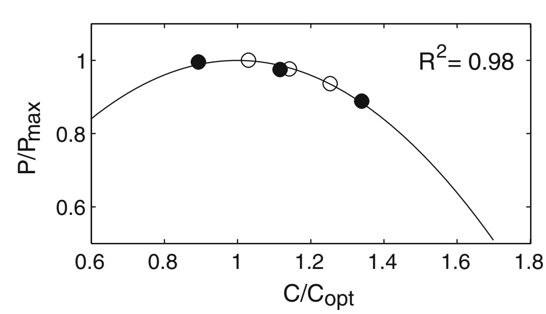

Fig. 7 Power output in relation to cadence. Mean power output and cadence from two studies (*filled circles* Mora-Rodriguez and Aguado-Jimenez 2006; *open circles* Watson and Swensen 2006) were normalized relative to their estimated individual maximal power output for endurance cycling and corresponding individual optimal cadence assessed with a quadratic fit of the data. The solid line shows the quadratic regression constrained to pass through the origin ($R^2 = 0.98$; $P < 0.001$)

there are two explanations for this increase of C_{opt} with increasing performance level: (1) the increased ratio of P_{ext} to P_{tot} and (2) the recruitment of additional fast-twitch muscle fibers. With our simplified model, the ratio of the increase caused by the first mentioned factor to the total increase of C_{opt} found in the experimental data can be estimated. The P_{ext}–cadence relationship with P_{max} and C_{opt} corresponding to the mean values found in the experimental tests at LT_3 can be simulated with the model by setting k_2, k_4 and k_5 to zero and by adjusting the other model parameters (the constants k_1, k_3 and Z of the muscles). Thereafter, by increasing only the activation level Z of the muscles to reach P_{max} corresponding to the measured value at LT_4, the increase of C_{opt} caused by the increased ratio of P_{ext} to P_{tot} can be established. With the mean values of P_{max} and C_{opt} from the experimental tests, the simplified model predicts the amount of the increase caused only by the ratio of P_{ext} to P_{tot} to be about 50% of the total increase of C_{opt}. This value is only a mean value for the subjects tested in this study at the analyzed performance levels and shows great variability that could be attributed to the individual differences in the fiber type composition of the muscles and to the analyzed performance levels.

Knowledge about the effect of cadence on endurance performance is relevant not only for competitive cyclists but also for investigations using cycling tests. In laboratory testing, different threshold determinations are routinely used without always having a close control for pedaling cadence. Furthermore, the knowledge of the effect of different factors (e.g., performance level) on this P_{ext}–cadence relationship or especially on C_{opt} is also important for cyclists and investigators. Our experimental results illustrated a shift of C_{opt} with increasing performance level and the individuality of C_{opt}. Our theoretical model contains some individual intrinsic factors (coordination, fiber type composition, and moment arms of the muscles) that could explain the experimentally detected shift and individuality of C_{opt}. In addition to these factors, some external factors could also have a significant influence on C_{opt}. With the method to assess individual P_{max} and C_{opt} proposed in this study, the influence of such factors on C_{opt} can be analyzed in experimental studies. The factors of interest for cyclists and scientists could include altitude, temperature, road incline, racing position, saddle height, and crank length.

Conclusion

This study showed that the mechanical external power–cadence relationship for endurance cycling can be well fitted with a quadratic regression constrained to pass through the origin. The mean calculated 95% confidence interval for assessing individual maximal power output and the corresponding optimal cadence was 3.4 and 7.5% at lactate thresholds with fixed blood lactate concentrations of 3, 3.5, and 4 mmol L^{-1}. The knowledge of the effect of cadence on endurance performance is relevant not only for competitive cyclists but also for investigators using cycling tests. Furthermore, with the proposed method, the effect of influencing factors on this mechanical external power–cadence relationship, especially on optimal cadence, can be adequately analyzed in future research.

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